Global assessment of atmospheric river subseasonal prediction skill

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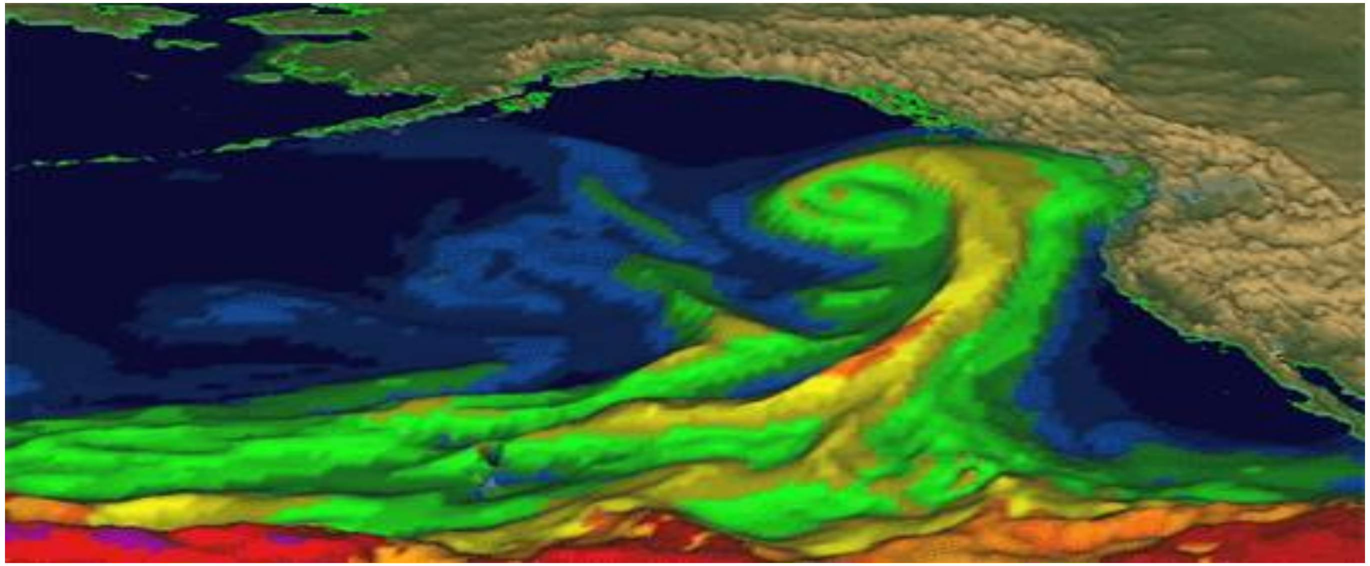
Contains key figures/concepts from:

1. DeFlorio et al. 2017, **Global assessment of atmospheric river prediction skill**, J. Hydromet. (in revision)
2. DeFlorio et al. 2017, **Global evaluation of atmospheric river subseasonal prediction skill**, Clim. Dyn. (in prep)
3. Guan and Waliser 2015, **Detection of atmospheric rivers: Evaluation and application of an algorithm for global studies**, J. Geophys. Res., **120**, 12514-12535.

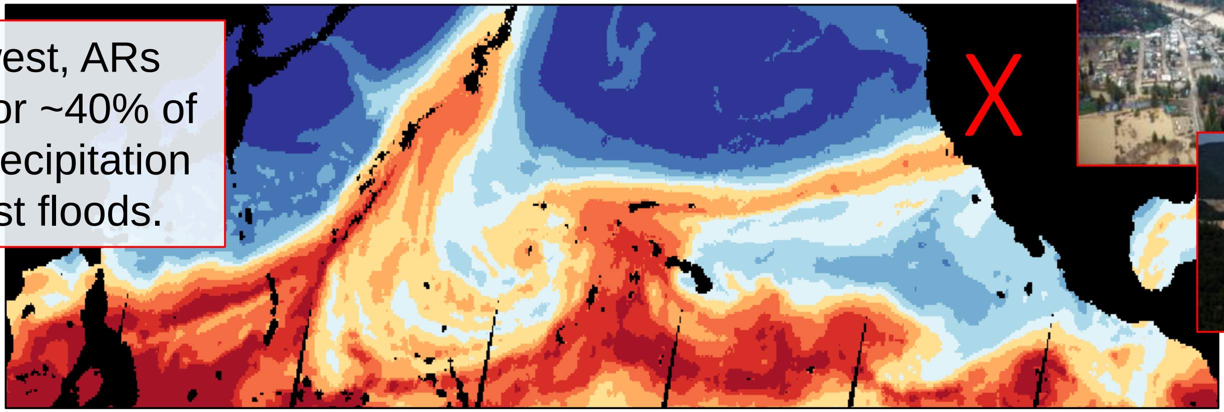
Atmospheric rivers and their associated flood and hazard risks occur globally and influence climate and water extremes.



NOAA ESRL

Over 90% of poleward moisture transport at midlatitudes is by ARs that take up only ~10% of the zonal circumference (Zhu and Newell 1998).

In the west, ARs account for ~40% of annual precipitation and most floods.



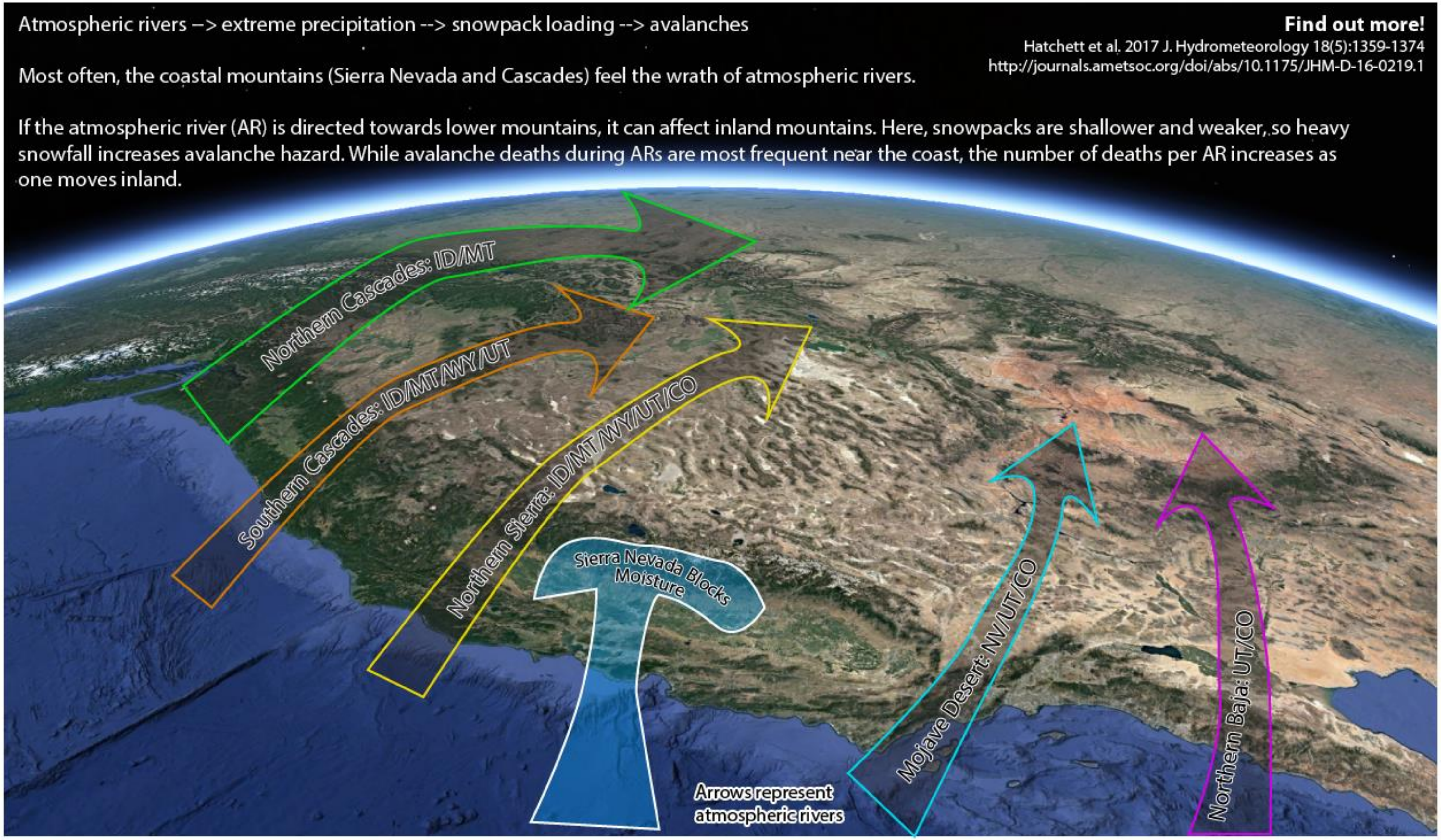
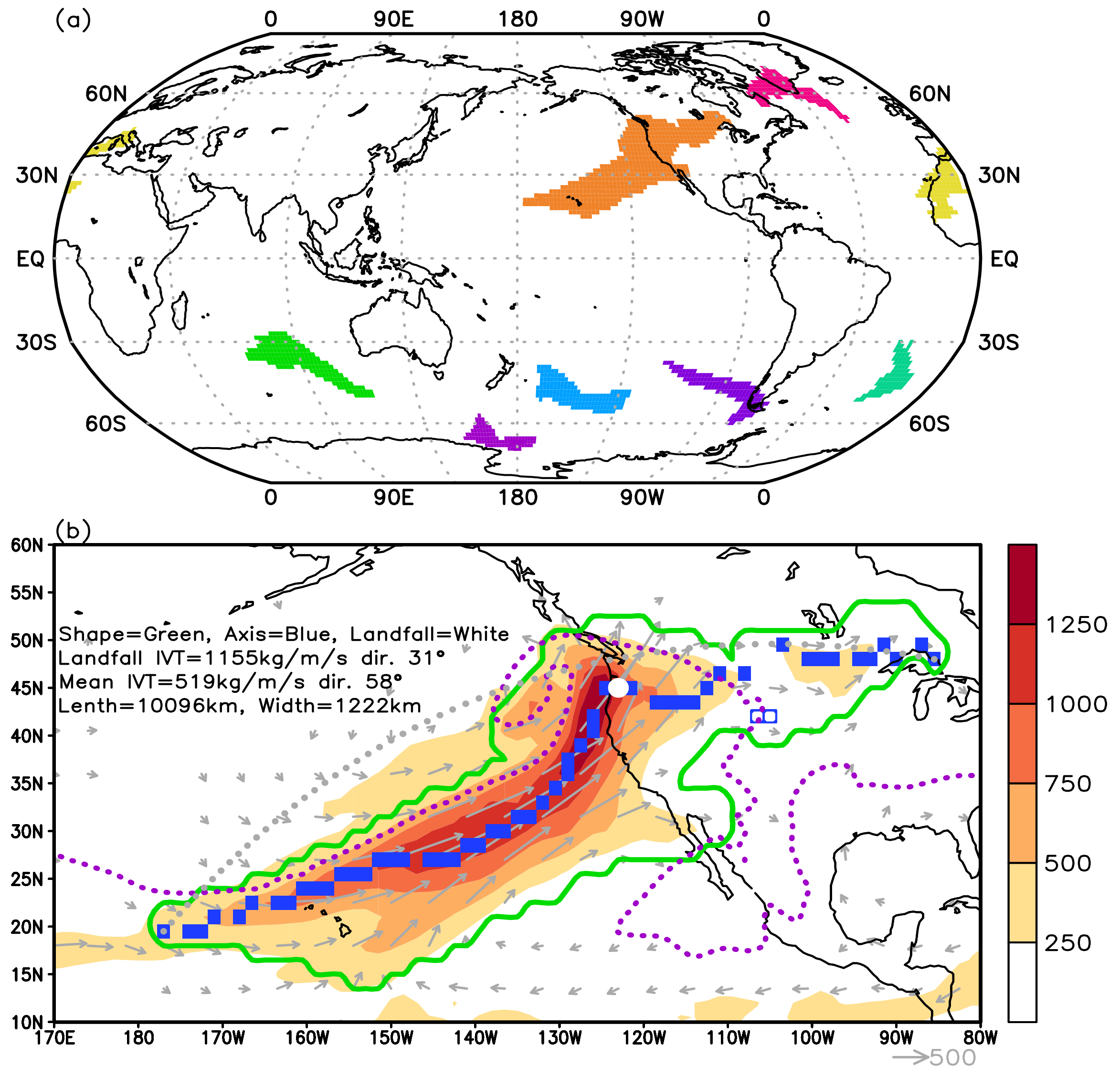


Figure from Desert Research Institute

A global, objective algorithm for AR identification

(Guan and Waliser 2015)

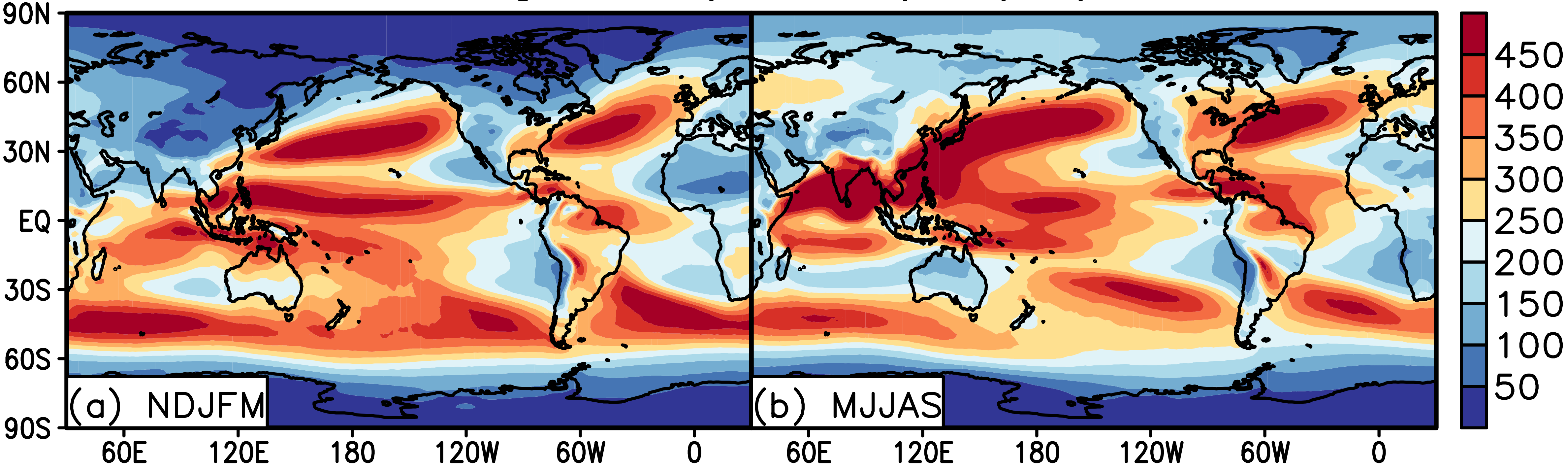


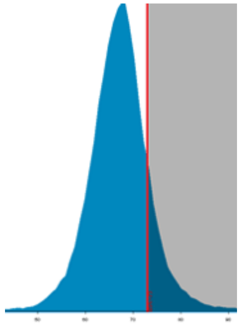
- Based on Integrated Vapor Transport (IVT) fields and a number of common AR criteria (e.g. Ralph et al. 2004)
- Applied to global hindcast/forecast systems and reanalysis datasets
- Code and databases available at: https://ucla.box.com/ARcatalog
- Databases include AR Date, $IVT_{x,y}$, Shape, Axis, Landfall Location, etc.
- Used for GCM evaluation (Guan et al. 2017, in revision), climate change projections (Espinoza et al. 2017, submitted), & forecast skill assessment (DeFlorio et al. 2017a and 2017b, in revision)

Global AR Climatology

Guan and Waliser 2015

Based on Integrated Vapor Transport (IVT), 1997-2014





Intensity threshold:

IVT > max(85th percentile, 100 kg m-1 s-1)

Geometry threshold:

Length > 2000 km, Length/Width > 2

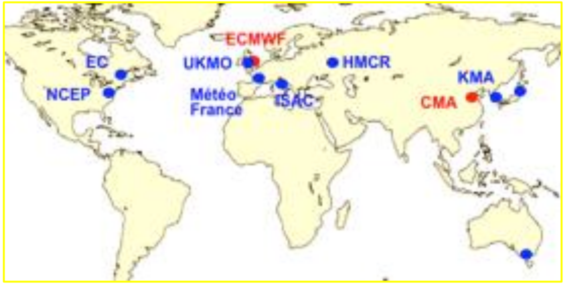
Key Research Question

What is the limit of subseasonal (1-week to 1-month) prediction skill of 2-week AR occurrence, and how does it vary as a function of season, region, and certain large-scale background climate conditions?

The S2S database: our toolbox for assessing global AR subseasonal prediction skill

- Suite of real-time forecasts and several decades of hindcasts from 11 operational forecast models
- Maximum lead time ranging from 32 days to 60 days
- Hindcast ensemble size ranging from 1 to 33
- Variety of forecasting configurations and other model parameters (heterogeneity amongst models)
  - "dataset of opportunity"

The S2S Database: a joint WCRP-WWRP Project



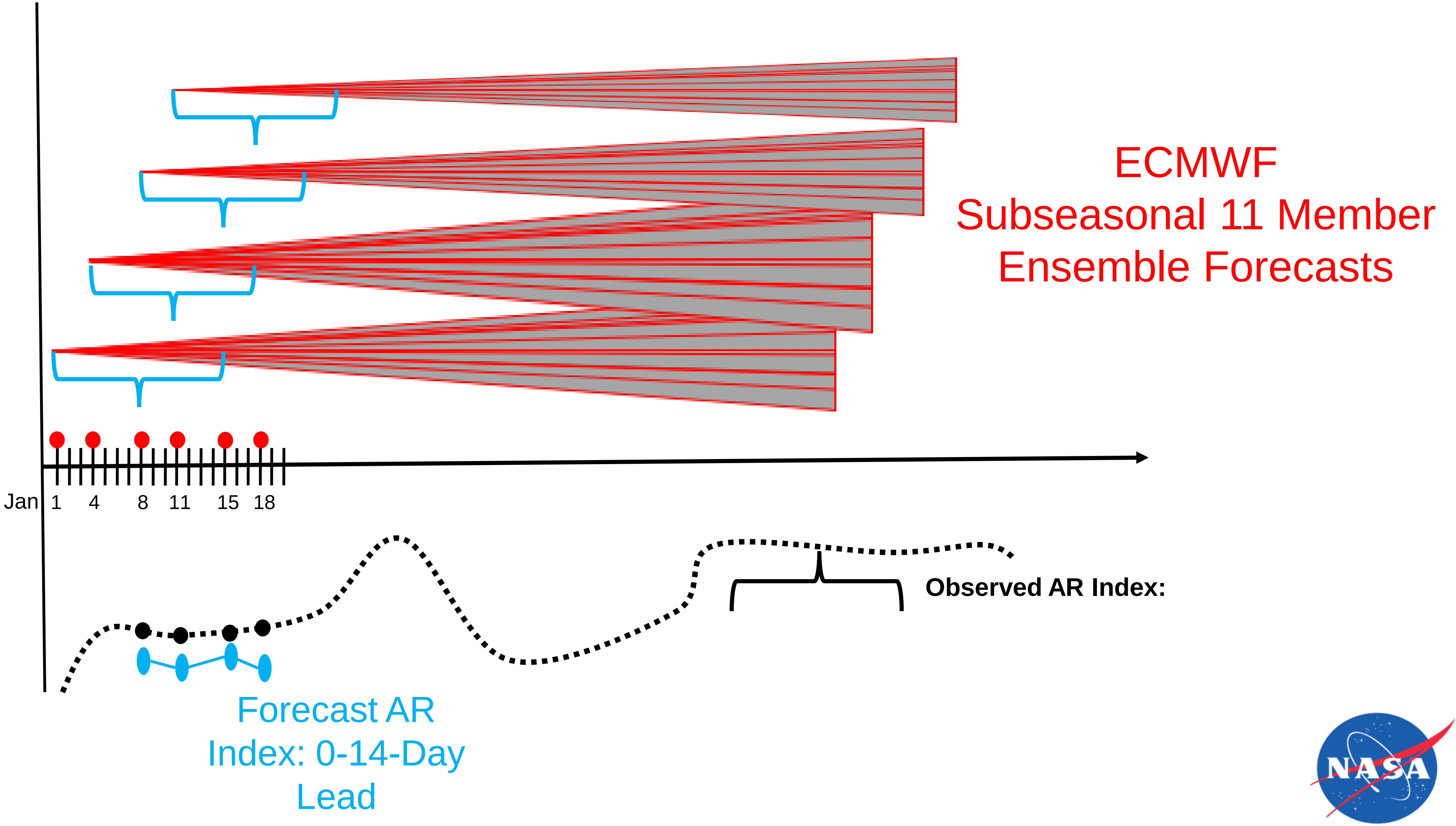
	Time-range	Resol.	Ens. Size	Freq.	Hcsts	Hcst length	Hcst Freq	Hcst Size
ECMWF	D 0-46	T639/319L91	51	2/week	On the fly	Past 20y	2/weekly	11
UKMO	D 0-60	N216L85	4	daily	On the fly	1996-2009	4/month	3
NCEP	D 0-44	N126L64	4	4/daily	Fix	1999-2010	4/daily	1
EC	D 0-32	0.6x0.6L40	21	weekly	On the fly	1995-2014	weekly	4
CAWCR	D 0-60	T47L17	33	weekly	Fix	1981-2013	6/month	33
JMA	D 0-34	T319L60	25	2/weekly	Fix	1981-2010	3/month	5
KMA	D 0-60	N216L85	4	daily	On the fly	1996-2009	4/month	3
CMA	D 0-45	T106L40	4	daily	Fix	1886-2014	daily	4
CNRM	D 0-32	T255L91	51	Weekly	Fix	1993-2014	2/monthly	15
CNR-ISAC	D 0-32	0.75x0.56 L54	40	weekly	Fix	1981-2010	6/month	1
HMCR	D 0-63	1.1x1.4 L28	20	weekly	Fix	1981-2010	weekly	10

Vitart et al. 2016

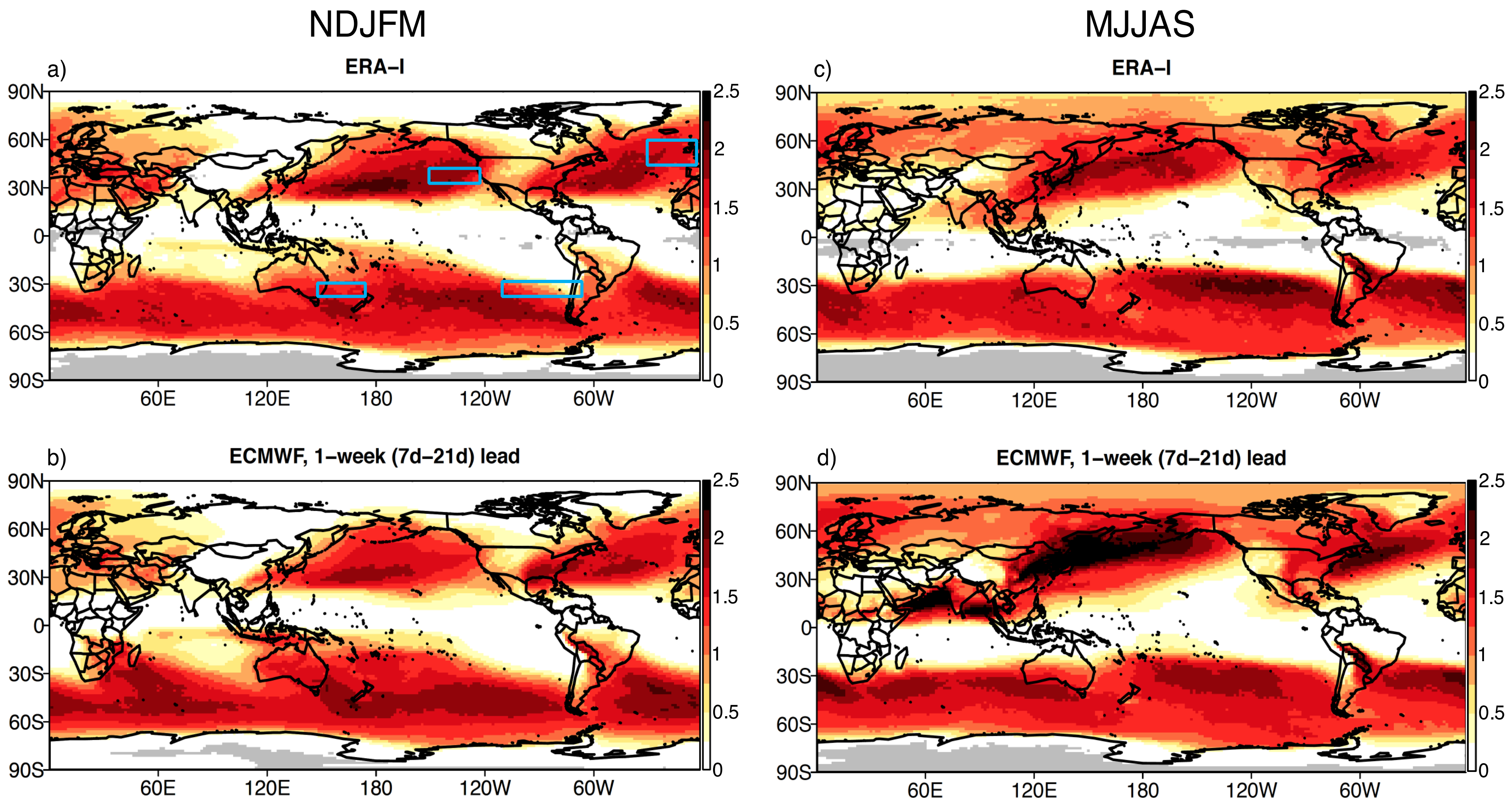
Goal #2: use objective identification algorithm to assess global AR subseasonal prediction skill at lead times of 1-week to 1-month using S2S hindcast data

DeFlorio et al. 2017, **Global evaluation of atmospheric river subseasonal prediction skill**, Clim. Dyn. (in prep)

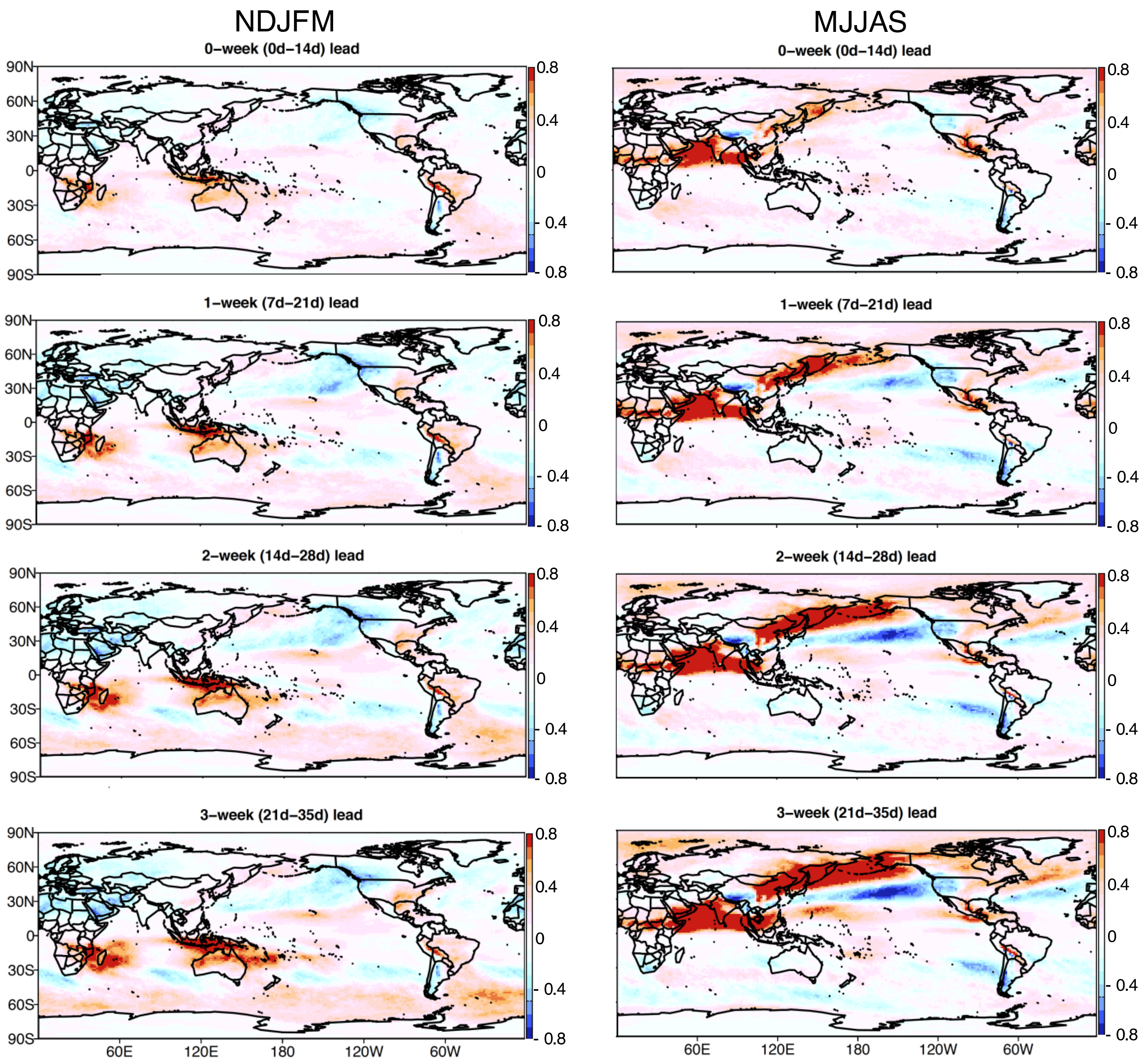
Subseasonal AR Prediction using ECMWF S2S Hindcasts



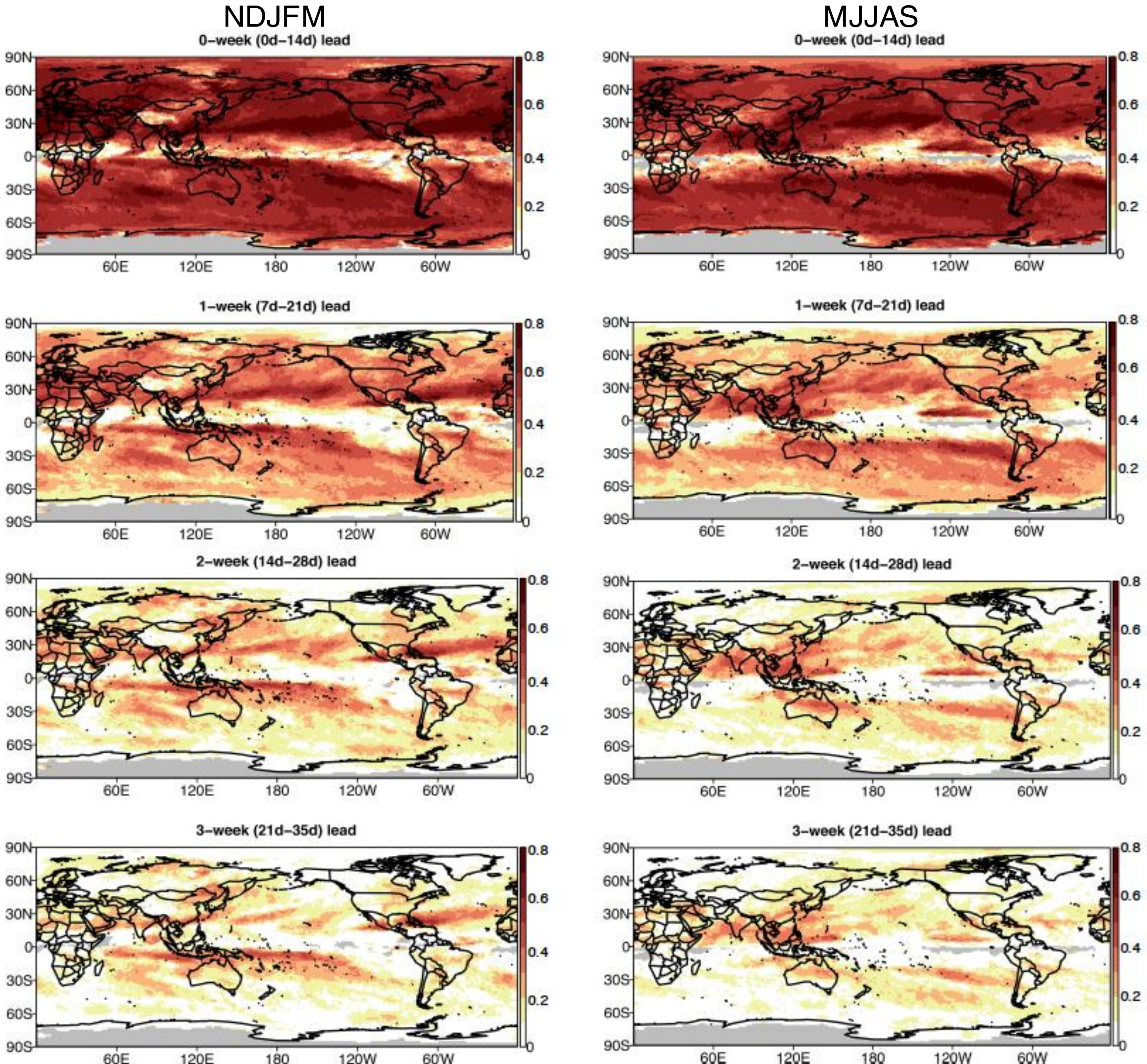
AR Occurrence Climatology *(#AR days per two weeks)*



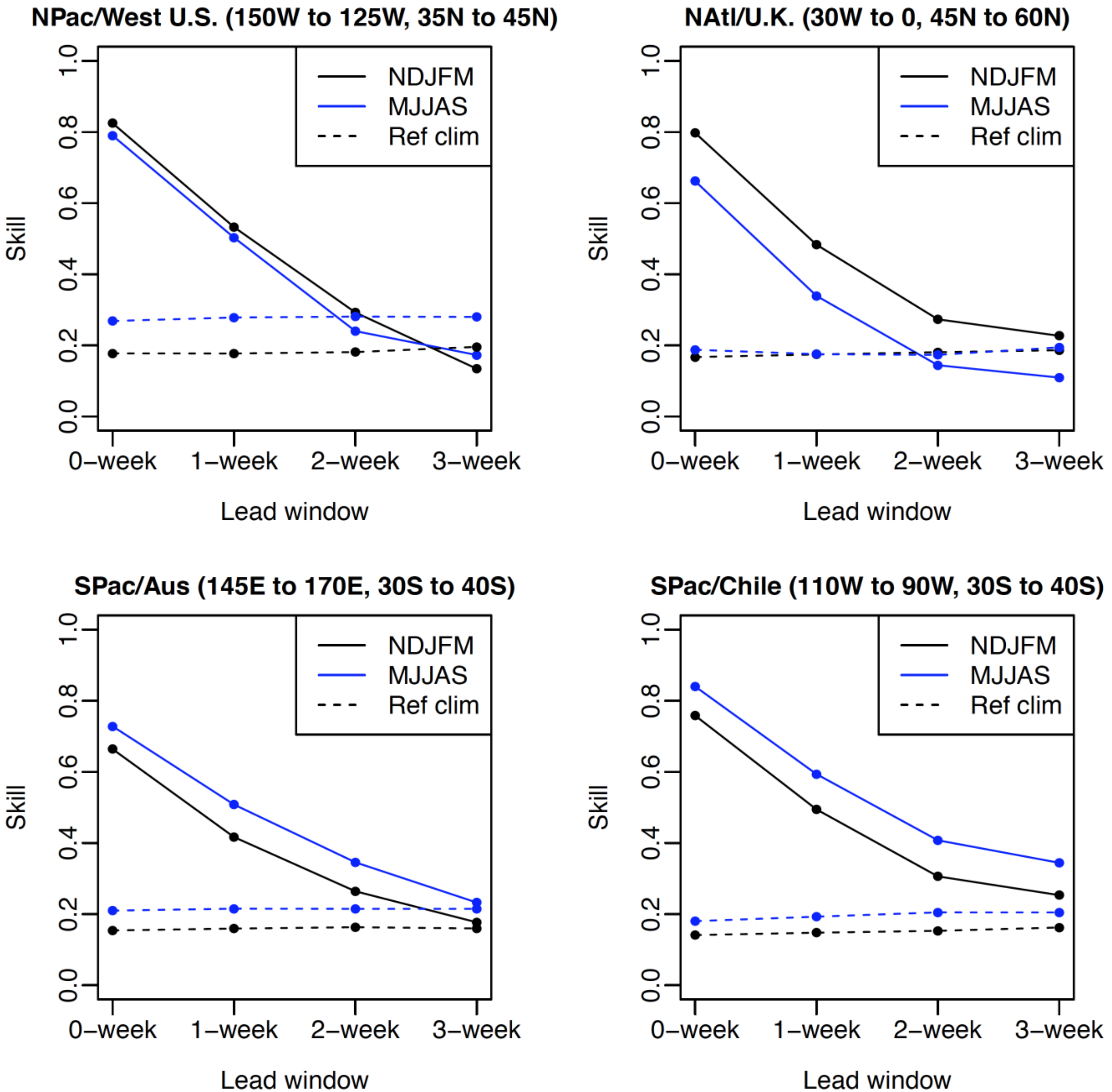
ECMWF Minus ERA-I AR Occurrence



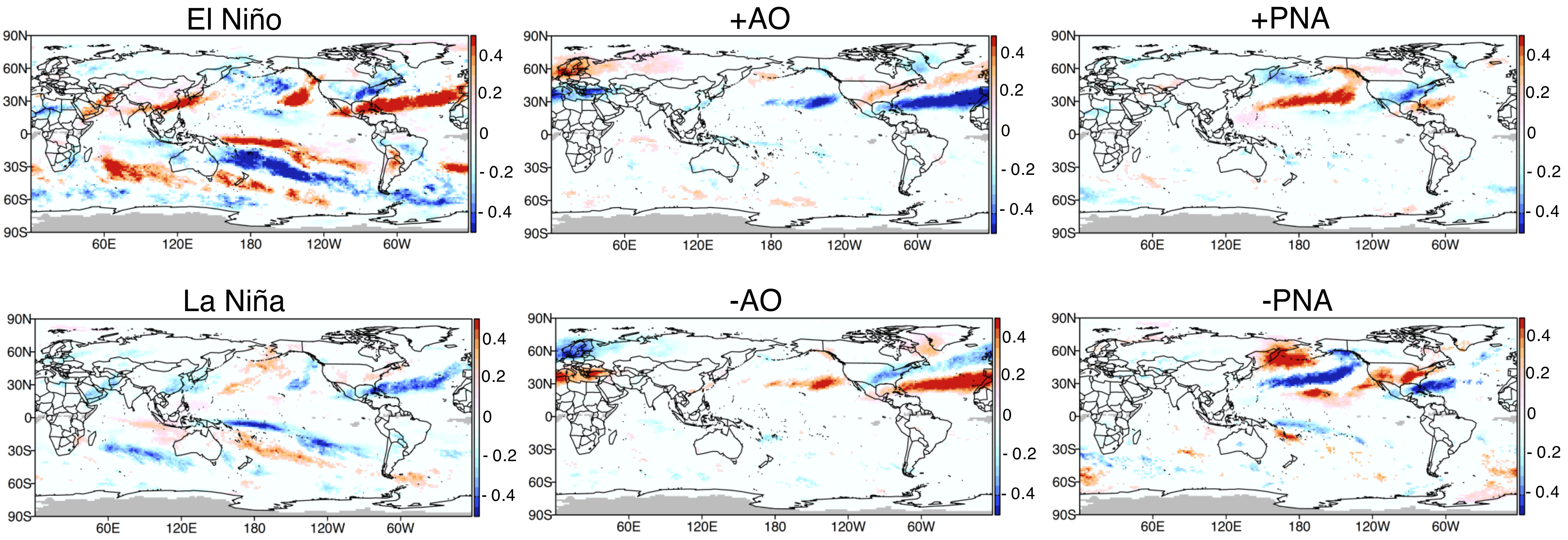
AR Occurrence Forecast Skill



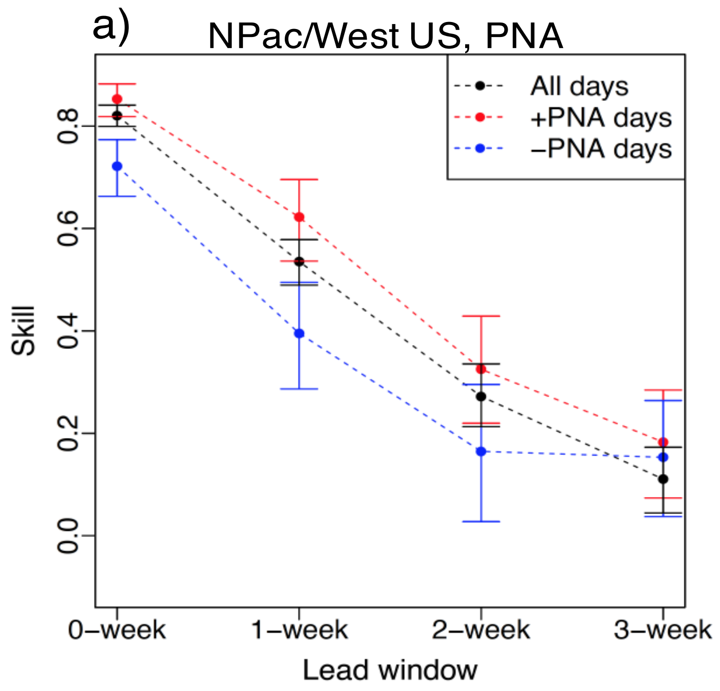
AR Occurrence Forecast Skill vs. Lead

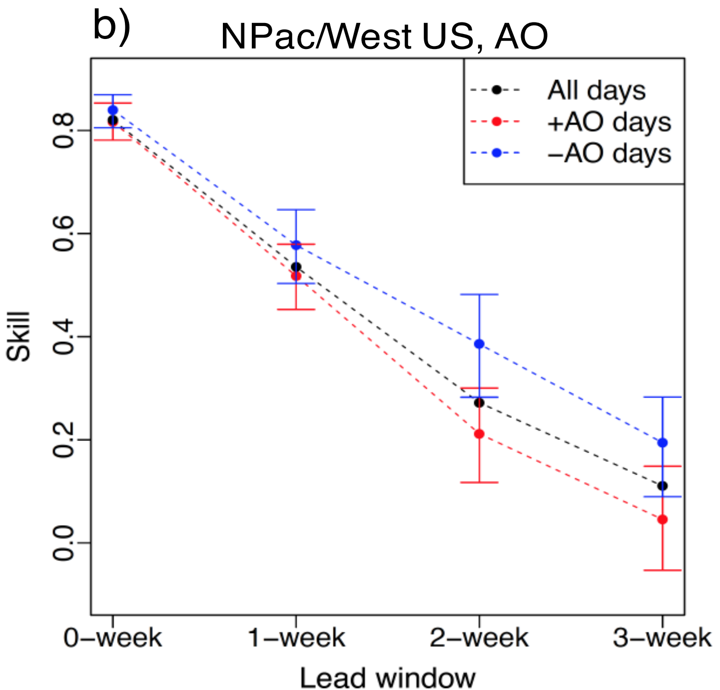


NDJFM AR2wk Occurrence Anomalies: ENSO, AO, and PNA, ERA-I

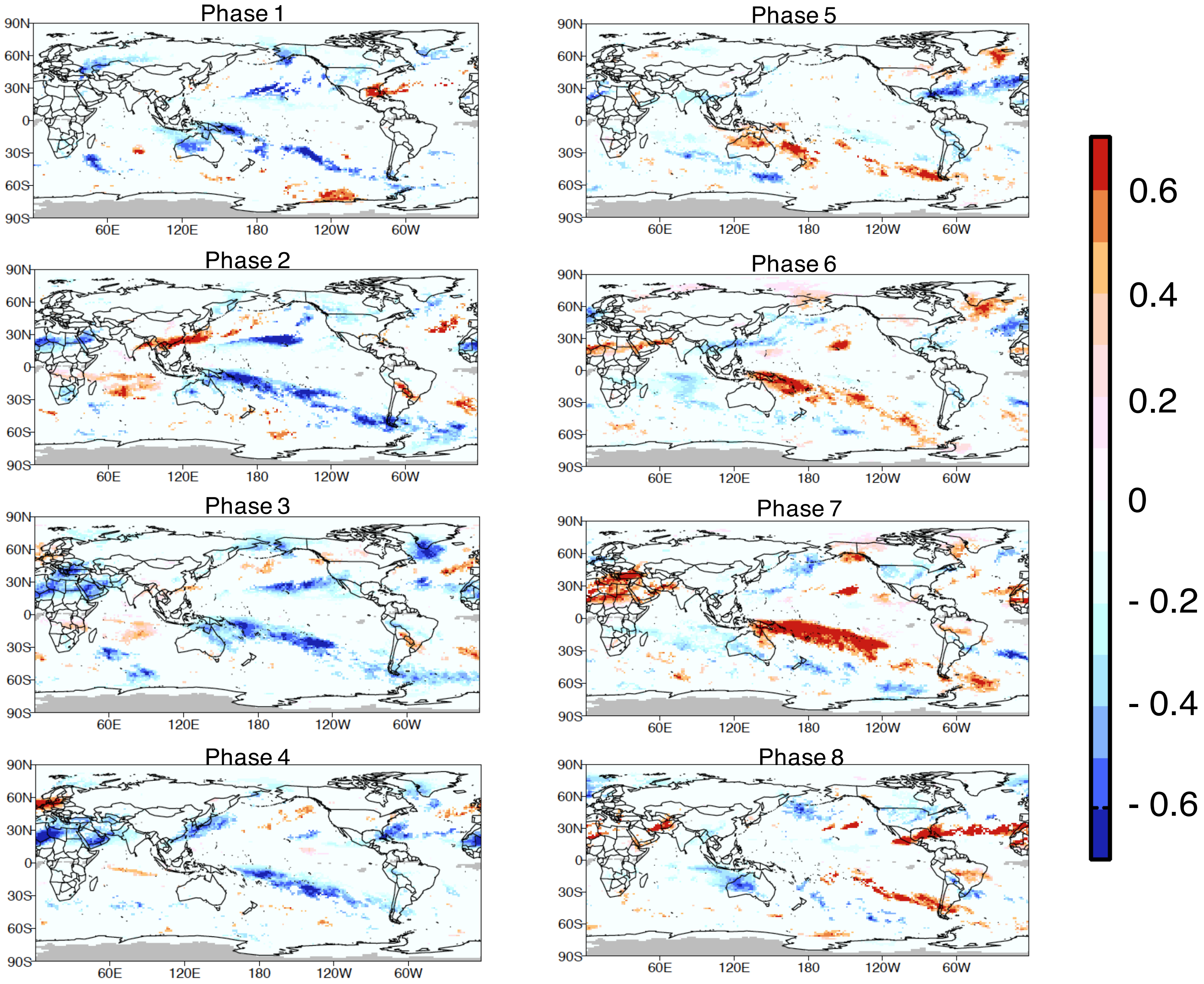


NDJFM AR2wk Occurrence Forecast Skill: Climate Mode Composites

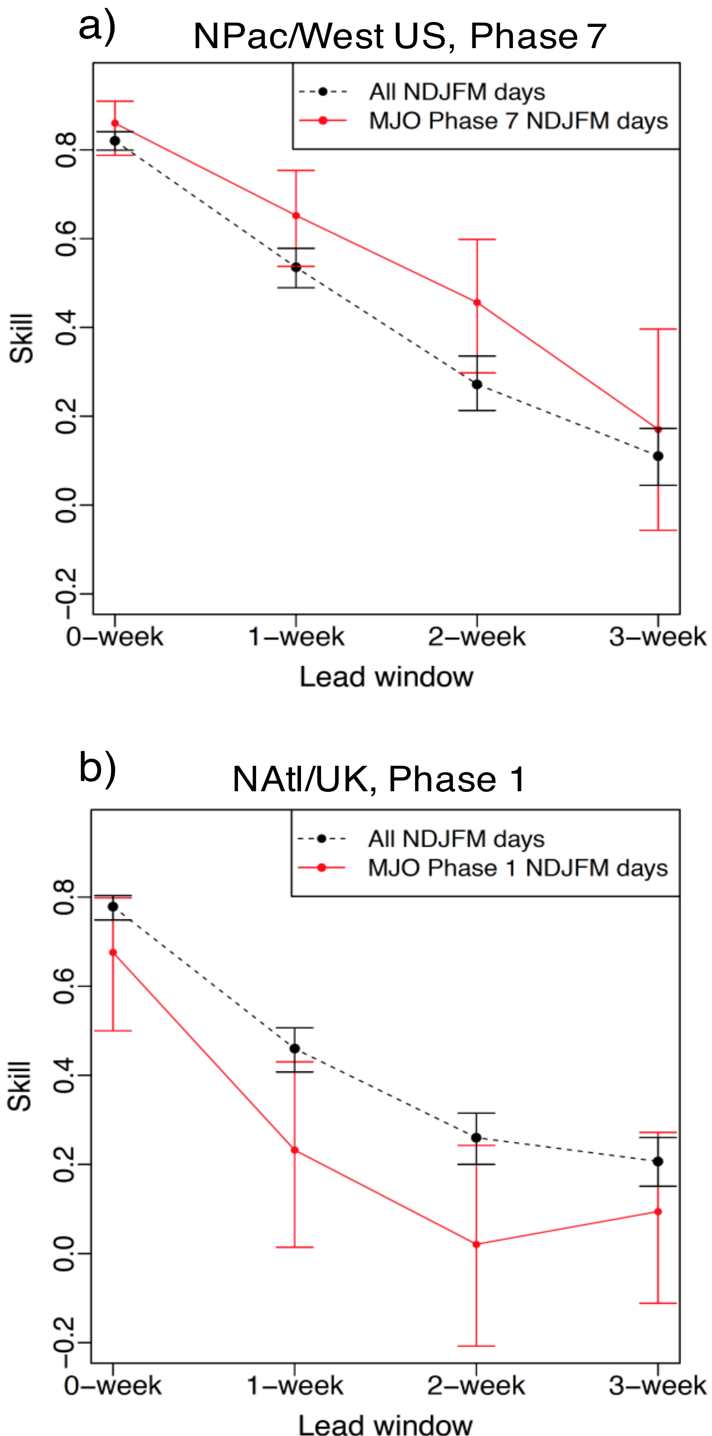




NDJFM AR2wk Occurrence Anomalies: MJO, ERA-I



NDJFM AR2wk Occurrence Forecast Skill: MJO Phase Composites



Summary: subseasonal AR prediction skill

- Subseasonal (1-week to 1-month lead time) AR prediction skill evaluated globally for the first time (DeFlorio et al. 2017, in prep)
  - counts #AR days per two weeks as a function of lead time ("AR2wk"); necessary to use an aggregate statistic for subseasonal prediction of chaotic, episodic events
- Observed pattern of seasonal mean of AR2wk strongly resembles global pattern of daily AR frequency (Guan and Waliser 2015)
- Large model biases of up to 1-2 AR days per 2 weeks over Kuroshio Extension and Indian Monsoon regions in MJJAS
- ECMWF forecast system outperforms a reference skill forecast based on monthly climatology at 1-week (7-day to 21-day lead window) in all four global regions; up to 2-week (14-day to 28-day lead window) in South Pacific regions

- Higher prediction skill over the North Pacific/Western U.S. region:
  - at 0-week and 1-week lead time during +PNA relative to –PNA
  - at 1-week and 2-week lead time during MJO phase 7 relative to "all days" forecast (but not quite at 95% confidence)

Ongoing and Future Work

- Experimental real-time subseasonal (2-week lead) forecasts of western U.S. AR frequency and intensity using ECMWF and NCEP forecast systems
    - Collaboration with CW3E at UCSD-SIO
        - Marty Ralph
        - Aneesh Subramanian
        - Sasha Gershunov

- Multi-model evaluation of subseasonal AR prediction skill